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# Efficient Micro-Doppler based pedestrian activity classification for ADAS systems using Krawtchouk moments

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### Abstract

In this paper the application, performance and results of a fully discrete micro-Doppler feature classification processing chain utilising Krawtchouk moment invariants are presented. The approach demonstrates to be capable of running on low power hardware such as the Raspberry Pi 2. The effectiveness of the proposed approach is verified through the use of real K-band data in real-time.

## 1. Introduction

Future automotive autonomous systems require contextual information about the scene at hand to allow complex decision making in the context of self-driving cars. Secondary motion in reference to the bulk motion described by the Doppler effect are known as micro-Doppler (m-D) modulations (Chen (2011)), which can be captured by using time-frequency radar signatures containing unique information about moving non-rigid targets such as pedestrians in the line-of-sight (LOS). In contrast to information captured by camera systems, radar signatures are insensitive to light conditions, weather conditions and relative distance. They can be therefore a robust identifier for scene and target classification, which can be used in safety critical applications if they meet performance requirements.

The main contribution of this paper is the presentation of a novel radar m-D classification tool-chain capable of running on low-power hardware using Krawtchouk moments enabling real-time operation of the classification algorithm by Clemente et al. (2016). Captured real radar data is sensitive to noise and variant to the initial phase of capture, rotation, scale and translation. Further, they are highly complex and thus it is computationally expensive to perform any further processing, specifically in the context of classification. To address these issues, a processing tool chain has been developed utilising five steps to reduce the data complexity and ultimately yielding a robust feature vector. With the ability to highly parallelise these steps on compatible hardware, it enables real-time pedestrian classification with a Raspberry Pi 2 on simultaneously captured real K-band radar data on a trained classifier containing four classes of pedestrians.

The remainder of this paper is organised as follows. Section 2 introduces the feature extraction using Krawtchouk moments. Section 3 describes the potential application in autonomous systems, while Section 4 presents the performance of the system. Section 5 concludes this paper.

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## 2. Feature Extraction

Safety critical systems require information with as little delay as possible and in near real-time. It is therefore of interest to use feature vectors with a minimal number of components, while maintaining a robust set of information. It is further advantageous if the feature extraction is computationally efficient and ideally based on as many pre-computed components as possible. One such processing chain has been proposed (Clemente et al. (2016)) to extract a robust feature vector with pre-computed Krawtchouk polynomials resulting in Krawtchouk moment invariants, which are further invariant to rotation, scale and translation of the image.

Given a discrete sequence of complex radar data $\mathbf{x(n)} = \mathbf{I(n)} + \mathbf{jQ(n)}$, this vector is normalised and downsampled to reduce the initial amount of data and limit the relevant frequency range dependent on the expected target signatures, resulting in the signal $\tilde{\mathbf{s}}(\mathbf{n})$. The spectrogram is computed using a discrete short-time Fourier transform resulting in

$$\chi(\nu, k) = |STFT(x)|^2 = \left| \sum_{n=0}^{N-1} (\tilde{s}(n) \cdot h(n-k) \cdot e^{\frac{-j2\pi\nu n}{N}}) \right|^2, k = 0, ..., K-1 \ , \tag{2.1}$$

where $\nu$ is the normalized frequency and $h$ is a windowing function of choice to smooth the edges of the each iterative signal window (Clemente et al. (2015)).

Invariance to the initial phase of motion is achieved by measuring the cadence of Doppler frequencies in $\chi(\nu, k)$, resulting in the cadence-velocity diagram (CVD),

$$\Delta(\nu, \epsilon) = \left| \sum_{k=0}^{K-1} (\chi(\nu, k) \cdot e^{\frac{-j2\pi k\epsilon}{K}}) \right|, \tag{2.2}$$

where $\epsilon$ is the cadence frequency and the size of this image is defined by the choice of the Fourier transform resolution, resulting in a $N \times K$ size, where $N$ is the vertical dimension of $\chi(\nu, k)$ (i.e. the Doppler frequency spectrum). For efficient classification the CVD must be further compressed while maintaining discrimination between separate feature classes and similarity within a particular class (Clemente et al. (2015), Bjőrklund (2012)).

To achieve this, geometrical moment invariants, as introduced by Hu (1962), can be used to transform the CVD into a compact feature vector. An orthogonal form using Krawtchouk polynomials was presented by Yap et al. (2003) and further applied by Clemente et al. (2016) to radar imaging in a discrete fashion, by applying pre-computed weighted Krawtchouk polynomials $\bar{K}$ of the order (p,q) to $\Delta(\nu, \epsilon)$ (2.2) resulting in the Krawtchouk moments of a CVD,

$$Q_{pq} = \sum_{\nu=0}^{P-1} \sum_{\epsilon=0}^{Q-1} \bar{K}_p(\epsilon; p_1, P-1) \bar{K}_q(\nu; p_2, Q-1) \Delta(\nu, \epsilon). \tag{2.3}$$

The above expression can be readily vectorised to

$$\mathbf{F}_{\text{Krawtchouk}} = [Q_{00}, ..., Qpq]. \tag{2.4}$$

This unique feature vector is further normalised to remove the impact of singular features over others and hence potential bias in the classification process, resulting in the final feature vector of dimension $(p+1) \times (q+1)$ being

$$\tilde{\mathbf{F}} = \frac{\mathbf{F} - \mu_{\mathbf{F}}}{\sigma_{\mathbf{F}}}, \tag{2.5}$$

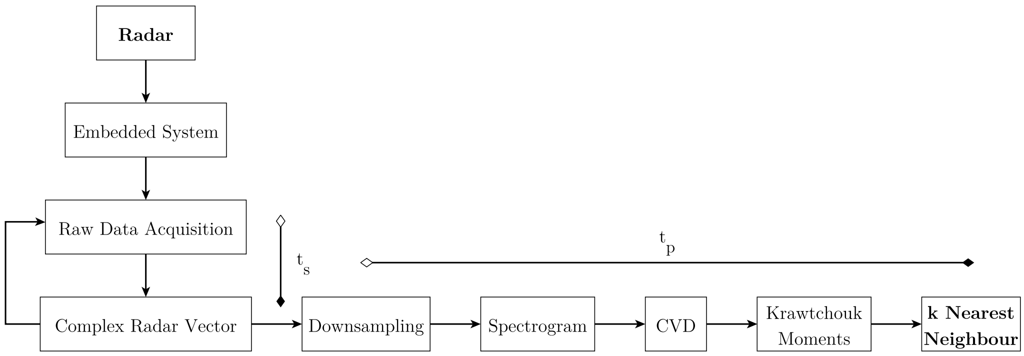


Figure 1: Processing chain of a Python based efficient mD classification on an embedded system, where $t_s$ is the sample time and $t_p$ is the total processing time of the algorithm.

where $\mu_{\mathbf{F}}$ is the mean and $\sigma_{\mathbf{F}}$ is the standard deviation of $\mathbf{F}$. This robust feature vector is invariant to rotation, scale and translation of an image and can be computed discretely and efficiently for classification purposes (see Clemente et al. (2016) for more detail).

## 3. Applications

The procedure in section 2 was implemented in a modular processing tool-chain in Python capable of running on a variety of hardware including low-power embedded systems. The modular nature of the processing chain allows parallel computing to be employed for both complete processes and further sub-processes itself. The standard processing flow is shown in Figure 1.

The primary requirement for this processing chain is a radar sensor which provides phase information in the form of I/Q radar data, which can be interfaced with the desired processing system.

This enables flexible deployment of m-D analysis and radar analysis in a variety of applications. The experiments in this paper were conducted using a 24 GHz radar sensor at a height of 1 metre being a typical automotive placement above the front bumper. It allows robust analysis of the scene at hand to detect and classify objects in motion. The focus in the following section was given to pedestrian motion. This requires an effective Doppler frequency range of $\pm 750$ Hz for pedestrians running in front of a vehicle (Ghaleb et al. (2008)). It is further suggested by Bjőrklund (2012) to capture a full cycle of pedestrian motion, which was modestly estimated at 3 seconds. Being able to classify pedestrians and their current type of motion can be an important measure for autonomous systems and driver assistance as it allows to not only to make an assessment of the current scene but further allows to predict future movement of pedestrians based on their direction and their relative velocity making it a potentially useful measure in future automotive systems.

## 4. Experimental Results

Data was recorded for the four classes as shown in Table 1. The data was then processed to CVDs (examples shown in Figure 2 with associated spectrograms) and classified in Krawtchouck moment data sets. The integrity of the data was verified using a Monte Carlo approach and a k-Nearest-Neighbour (kNN) classifier with a 70/30 split. Hence,

| Class | Time recorded | Training yield |
|---|---|---|
| Individual walking | 352.9 s | 77 |
| Individual running | 319.8 s | 73 |
| Group walking | 179.4 s | 61 |
| Group running | 221.9 s | 56 |
| All classes | 1074 s | 267 |

Table 1: Recorded amount of raw data for the 4 tested classes

| | Platform | k=1 | k=3 | k=5 | k=7 |
|---|---|---|---|---|---|
| Accuracy | all | 98.17% | 97.75% | 96.39% | 93.33% |
| Average time | x86 (Intel C2D T7500, 4GB RAM) | 0.173 s | 0.176 s | 0.172 s | 0.178 s |
| Average time | BeagleBone Black | 2.60 s | 2.73 s | 2.64 s | 2.74 s |
| Average time | Raspberry Pi 2 (1 GHz) | 1.72 s | 1.78 s | 1.75 s | 1.80 s |

Table 2: Accuracy verification of kNN-classifier and training data for a range of k-Neighbours

70% of the training data used was randomly selected and 30% was randomly selected as the testing set. The offline performance was then tested on 3 platforms, as shown in Table 2. The integrity of the data set was sufficient at above 90%. Further, given a sampling time $t_s$ of 3 seconds the Raspberry Pi 2 as a modern and low-power embedded systems is capable of running the classification in parallel to the data acquisition and can therefore provide classification predictions in quasi-real-time. It further indicates that the sampling time can be further reduced to match the processing time of the hardware to be used, illustrating the scalability of the proposed tool-chain.

The Raspberry Pi 2 and the radar sensor were successfully tested in a live environment being powered by a 5000 mAh battery, illustrating the low power requirements of the system with a projected runtime of the entire system at above an hour, demonstrating the power efficiency crucial in e.g. electric cars. The live testing showed no slow-down in comparison to the aforementioned offline performance.

## 5. Conclusion

In this paper the application, performance and results of a fully discrete micro-Doppler feature classification processing chain utilising Krawtchouk moment invariants was presented. The approach demonstrates to be capable of running on low power hardware such as the Raspberry Pi 2. The effectiveness of the proposed approach was verified through the use of real K-band data in quasi-real-time.

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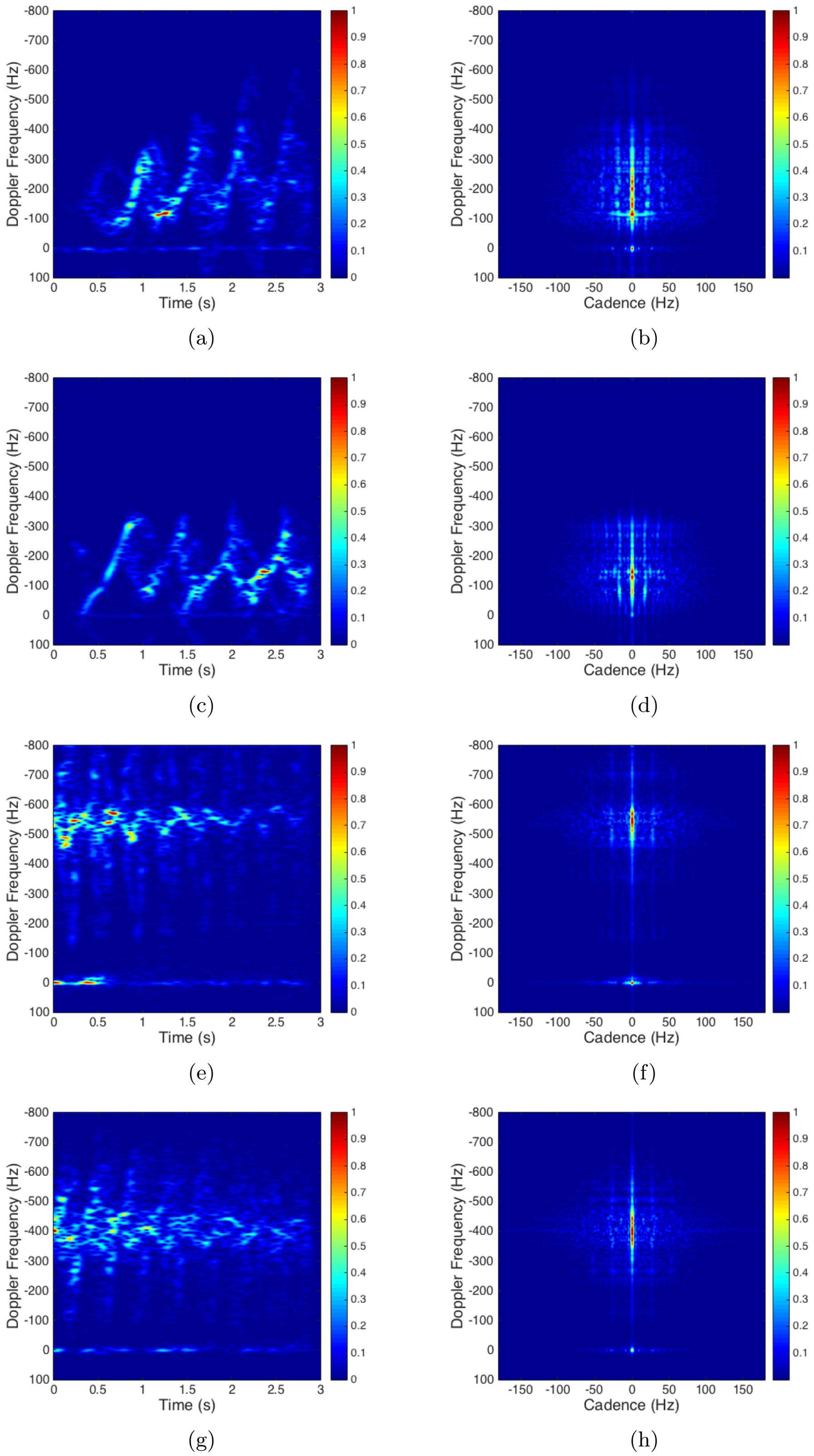


Figure 2: Spectrogram (LHS) and CVD (RHS) examples for recorded motion classes: (a,b) Single pedestrian walking, (c,d) multiple pedestrians walking, (e,f) single pedestrian running and (g,h) multiple pedestrians running.